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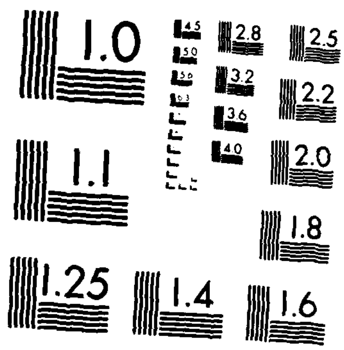

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Modeling Episodic Time Series*

by

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A particular form of filtered Poisson process (Parzen (1962b), p.159) is suggested for modeling time series data that contain episodes, i.e. large, exponentially decaying excursions away from baseline values of the series. The properties of this process are derived and the principle of conditional least squares estimation (Klimko and Nelson (1978)) is used to obtain consistent, asymptotically normal estimators of the average excursion heights and the decay rate parameter. The method is illustrated using hormone levels data.

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1. INTRODUCTION

Let $\{X_t, t=0, \pm 1, \pm 2, \ldots\}$ be a discrete time series, i.e. the X_t's are a collection of random variables with finite second moments. In analyzing time series data one usually assumes that X is covariance stationary, i.e. the mean value function $m_t = E[X_t]$ is a constant and that the covariance function $K(s,t) = \mathrm{Cov}[X_s, X_t]$ is only a function of $|s-t|$. Unfortunately, such an assumption rules out a wide class of interesting series. For example, Figure 1 is a graph of levels of Luteinizing hormone (LH) in a cow measured at ten minute intervals for 24 hours. It is difficult to imagine that this data comes from a covariance stationary time series. Even if it were the usual methods of time series analysis (correlation and spectral analysis) would not address the questions the scientist would be interested in, namely the intensity of episodic occurrence, the average heighth of episodes, and the rate at which the hormone level returns to its baseline value.

The features that distinguish this data (and other data in a wide variety of areas such as river flows, pollution levels, or chemical manufacturing processes) are the random occurrence of large surges followed by an exponential return to the low relatively constant baseline values. A model which reflects such behavior was suggested by Parzen (1962b). We assume that the process started at some time zero and let the number of episodes, $N(t)$, from time 0 to time t, $t \geq 0$, be a Poisson process with intensity parameter λ, i.e. for any $n \geq 1$ and any times $0 \leq t_1 < t_2 < \ldots < t_n$, $N(t_n) - N(t_{n-1}), \ldots, N(t_2) - N(t_1)$ are independent, Poisson distributed random variables with means $\lambda(t_n - t_{n-1}), \ldots, \lambda(t_2 - t_1)$. Then the value X_t of the process at time t is assumed to be of the form

$$X_t = \sum_{m=1}^{N(t)} y_m \, e^{-(t-\tau_m)/\gamma} \quad , \tag{1.1}$$

where the y_m's are iid random variables with mean μ_y and variance σ_y^2, while τ_m is the time of occurrence of the mth episode. Thus the time series consists of the sum of a random number of exponentially decaying spikes where the number of such spikes is governed by λ, their heighth by μ_y, and the rate of decay by γ. The aim of this paper is to provide good estimators of these parameters. In section two we derive the properties of the model (1.1) and in section three we find consistent, asymptotically normal estimators of λ, μ_y, and γ. In section three we will assume that γ is large enough relative to λ that one spike decays quickly enough before the occurrence of the next so that they do not overlap. This restriction seems reasonable for the type of data sets we are interested in. We also will assume that the baseline value is essentially constant. In many episodic time series the variation in the baseline is of importance also. Any method of analyzing such series would have to be iterative in nature, first considering the baseline and then the episodes. In this paper we consider only the episodes and leave the general problem to future research.

2. PROPERTIES OF THE MODEL

From (1.1) we can write

$$\begin{aligned} X_{t+1} &= \sum_{m=1}^{N(t+1)} y_m \; e^{-(t+1-\tau_m)/\gamma} \\ &= \sum_{m=1}^{N(t)} y_m \; e^{-1/\gamma} e^{-(t-\tau_m)/\gamma} + \sum_{m=N(t)+1}^{N(t+1)} y_m \, e^{-(t+1-\tau_m)/\gamma} \\ &= \rho X_t + \varepsilon_{t+1} \end{aligned}$$

where $\rho = e^{-1/\gamma}$ and the ε_t's are iid random variables since they are a function of $N(\cdot)$ for the nonoverlapping time intervals $(0,1]$, $(1,2]$, etc. Further, ε_{t+1} is independent of X_s for $s < t + 1$. Thus X is in the form of an autoregressive process of order one but as we shall see it is not covariance stationary. We note that for $0 < \gamma < \infty$, we have $0 < \rho < 1$.

Now for a poisson process with intensity λ we have that the arrival times $\tau_1, \ldots, \tau_K$ in the interval $[s,t]$ given that $N(t)-N(s) = K$ are iid uniformly distributed on the interval $[s,t]$. Thus

$$E[\varepsilon_t] = E_{N(t)-N(t-1)}\left\{E\left[\sum_{m=N(t-1)+1}^{N(t)} y_m e^{-(t-\tau_m)/\gamma} \middle| N(t)-N(t-1) = K\right]\right\}$$

$$= E_{N(t)-N(t-1)}\left[K\, E(y_m)\, E_{u(t-1,t)}\left(e^{-(t-\tau_m)/\gamma}\right)\right]$$

$$= E_{N(t)-N(t-1)}\left[K\mu_y\, \gamma(1-e^{-1/\gamma})\right]$$

$$= \lambda\mu_y\, \gamma(1-e^{-1/\gamma}) \quad ,$$

where $E_{u(t-1,t)}$ denotes expectation with respect to the Uniform $(t-1,t)$ pdf. Further,

$$E\left[\varepsilon_t^2 \middle| N(t)-N(t-1) = K\right] = K\; E(y_m^2)E_{u(t-1,t)}\left(e^{-2(t-\tau)/\gamma}\right)$$

$$+ K(K-1)\;[E(y_m)]^2\left[E_{u(t-1,t)}\left(e^{-(t-\tau)/\gamma}\right)\right]^2$$

$$= K(\mu_y^2+\sigma_y^2)\;\frac{\gamma}{2}\,(1-e^{-2/\gamma}) + K(K-1)\;\mu_y^2\;\gamma^2(1-e^{-1/\gamma})^2 \quad ,$$

and so

$$E[\varepsilon_t^2] = \lambda(\sigma_y^2 + \mu_y^2)\;\frac{\gamma}{2}\;(1-e^{-2/\gamma}) + \mu_y^2\;\gamma^2(1-e^{-1/\gamma}).\;\lambda^2 \quad ,$$

and

$$\mathrm{Var}[\varepsilon_t] = \lambda\delta\frac{\gamma}{2}\,(1-e^{-2/\gamma}) \quad ,$$

where $\delta = \mu_y^2 + \sigma_y^2$.

Now to find the moments of X_t we write

$$\begin{aligned} X_t &= \rho X_{t-1} + \varepsilon_t \\ &= \rho(\rho X_{t-2} + \varepsilon_{t-1}) + \varepsilon_t \\ &= \ldots \\ &= \rho^t X_o + \sum_{j=0}^{t-1} \rho^j\, \varepsilon_{t-j} \quad . \end{aligned}$$

Thus

$$\begin{aligned} E[X_t] &= \rho^t\, E[X_o] + \lambda\mu_y\gamma(1-e^{-1/\gamma}) \sum_{j=0}^{t-1} \rho^j \\ &= \rho^t E[X_o] + \lambda\mu_y\gamma(1-e^{-t/\gamma}) \quad . \end{aligned}$$

Also,

$$\begin{aligned} \mathrm{Cov}[X_t,X_{t+s}] &= \mathrm{Cov}[\rho^t\, X_o + \sum_{j=0}^{t-1} \rho^j\varepsilon_{t-j}, \rho^{t+s}X_o + \sum_{j=0}^{t+s-1} \rho^j\varepsilon_{t+s-j}] \\ &= \rho^{2t+s}\mathrm{Var}[X_o] + \mathrm{Var}[\varepsilon_t]\, \rho^s \sum_{j=0}^{t-1} \rho^{2j} \\ &= \rho^{2t+s}\, \mathrm{Var}[X_o] + \lambda\delta\frac{\gamma}{2}\, (1-e^{-2/\gamma})\, \rho^s(1-\rho^{2t})/(1-\rho^2) \\ &= \rho^{2t+s}\, \mathrm{Var}[X_o] + \lambda\delta\frac{\gamma}{2}\, \rho^s(1-\rho^{2t}) \quad , \end{aligned}$$

which gives

$$\mathrm{Var}[X_t] = \rho^{2t}\, \mathrm{Var}[X_o] + \lambda\delta\frac{\gamma}{2}\, (1-\rho^{2t}) \quad .$$

Thus X is indeed nonstationary. However, if one assumes that X_o has finite mean and variance and then lets t go to infinity, we have

$$\lim_{t \to \infty} E[X_t] = \lambda \mu_y \gamma \tag{2.1}$$

$$\lim_{t \to \infty} \mathrm{Cov}[X_t, X_{t+s}] = \lambda \delta \frac{\gamma}{2} \, e^{-s/\gamma}$$

$$\lim_{t \to \infty} \mathrm{Var}[X_t] = \lambda \delta \frac{\gamma}{2} \quad , \tag{2.2}$$

and X is asymptotically covariance stationary (see Parzen (1962a)). Note that letting t go to infinity is merely saying that we are observing the process after it has been going on for a long time.

3. CONDITIONAL LEAST SQUARES ESTIMATORS OF DECAY RATE AND AVERAGE HEIGHT

Since X_t is an asymptotototically stationary autoregressive process of order one, we can obtain consistent estimates $\hat{\rho}$, $\hat{\gamma} = -1/\log(\hat{\rho})$, and $\hat{\sigma}_\varepsilon^2$ of ρ, γ, and $\sigma_\varepsilon^2 = \mathrm{Var}[\varepsilon_t]$ by choosing $\hat{\rho}$ as the value of ρ minimizing

$$S(\rho) = \sum_{t=1}^{T-1} [(X_{t+1} - \bar{X}) - \rho(X_t - \bar{X})]^2 \tag{3.1}$$

and letting $\hat{\sigma}_\varepsilon^2 = S(\hat{\rho})/(T-1)$.

Unfortunately this procedure gives no information about λ and μ_y. However, it does motivate the use of conditional least squares.

If $\{Z_t, t=0,\pm 1,\ldots\}$ is an ordinary Gaussian autoregressive process of order one, i.e. $Z_t = a Z_{t-1} + \varepsilon_t$ where $E(\varepsilon_t) = 0$ and $\mathrm{Cov}(\varepsilon_t, \varepsilon_s) = \delta_{t-s}\sigma^2$ for the Kronecker delta function δ_v, then $E[Z_t | Z_{t-1},\ldots,Z_1] = a Z_{t-1}$. Thus the minimization of $\sum_{t=1}^{T-1} \{ Z_{t+1} - a Z_t\}^2$ can be thought of as minimizing the sum of squares of Z_{t+1} from its conditional expectation given all previous Z's. If Z is not Gaussian, the procedure provides the coefficients of the best linear approximation to this conditional expectation. In our situation we need to actually incorporate the conditional expectation into the function to be minimized so that estimators of λ and μ_y can be obtained. Thus we next derive this conditional expectation.

Since X_{t+1} is only a function of X_t and ε_{t+1}, it is Markov and $E[X_{t+1}|\, X_1,\ldots,X_t] = E[X_{t+1}|\, X_t]$. Further

$$E[X_{t+1}|X_t] = E[\rho X_t + \varepsilon_{t+1}|\, X_t]$$

$$= \rho X_t + E[\varepsilon_{t+1}\,|X_t] \quad .$$

But ε_{t+1} is independent of X_t so that

$$E[\varepsilon_{t+1}|X_t] = E[\varepsilon_{t+1}] = \lambda\mu_y\gamma(1-e^{-1/\gamma}) \quad .$$

Thus the conditional least squares estimators of λ,μ_y, and γ are chosen to minimize

$$\sum_{t=1}^{T-1} \{X_{t+1} - e^{-1/\gamma}\, X_t - \lambda\mu_y\gamma(1-e^{-1/\gamma})\}^2 \quad .$$

Unfortunately λ and μ_y only enter this function in their product and thus they are not identifiable. However, we do have another estimator of λ if we can count how many episodes occur in our data. Thus we will assume this is true and let $\hat{\lambda} = K/T$ where K is the number of episodes in data $X_1,\ldots,X_T$. Then we let $\beta = \lambda\mu_y$ and find $\hat{\gamma}$ and $\hat{\beta}$ to minimize

$$S(\gamma,\beta) = \sum_{t=1}^{T-1} \{X_{t+1} - e^{-1/\gamma}\, X_t - \beta\gamma(1-e^{-1/\gamma})\}^2 \quad . \tag{3.2}$$

To find the properties of these estimators we have the following Theorem, adapted in a straightforward way from Theorem 3.2 of Klimko and Nelson (1978).

<u>Theorem</u>

The estimators $\hat{\gamma}$, $\hat{\beta}$ obtained by minimizing (3.2) are consistent and

$$\sqrt{T}\begin{pmatrix}\hat{\gamma}-\gamma\\ \hat{\beta}-\beta\end{pmatrix} \xrightarrow{D} N_2(\underset{\sim}{0},\sigma_\varepsilon^2\, V^{-1})$$

where $\sigma_\varepsilon^2 = \mathrm{Var}[\varepsilon_t] = \lambda\delta\frac{\gamma}{2}\,(1-e^{-2/\gamma})$, and

$$V = \begin{bmatrix} a^2 \ \gamma(\frac{\lambda\delta}{2} + \beta^2) + 2ab\beta\gamma + b^2 & ac\beta\gamma + bc \\ ac\beta\gamma \ + bc & c^2 \end{bmatrix} ,$$

with

$$a = \gamma^{-2} e^{-1/\gamma} , \quad b = \beta[1-\gamma^{-1} \ e^{-1/\gamma}(1+\gamma)] \quad ,$$

$$c = \gamma(1-e^{-1/\gamma}) \quad .$$

Proof Theorem 3.2 in Klimko and Nelson (1978) shows that under certain regularity conditions that if a stochastic process X_t is Markov and asymptotically stationary and $g(\underset{\sim}{\theta}) = E[X_{t+1}|X_t]$ is a function of parameters $\underset{\sim}{\theta} = (\theta_1,\ldots,\theta_r)^T$ then the conditional least squares estimators $\hat{\underset{\sim}{\theta}}$ of $\underset{\sim}{\theta}$, based on observations $X_1,\ldots,X_r$, satisfy

$$\sqrt{T} \ (\underset{\sim}{\theta} - \underset{\sim}{\theta}) \longrightarrow N_r \ (\underset{\sim}{0}, \ V^{-1}WV^{-1})$$

where the (j,k)th elements of W and V are given by

$$W_{jk} = E\left[\{X_{t+1} - E[X_{t+1}|X_t]\}^2 \quad \frac{\partial E[X_{t+1}|X_t]}{\partial\theta_j} \quad \frac{\partial E[X_{t+1}|X_t]}{\partial\theta_k}\right]$$

and

$$V_{jk} = E\left\{\frac{\partial E[X_{t+1}|X_t]}{\partial\theta_j} \quad \frac{\partial E[X_{t+1}|X_t]}{\partial\theta_k}\right\} ,$$

$j,k=1,\ldots,r$. The unconditional expectations in these expressions are the asymptotic expectations.

In our situation,

$$\frac{\partial E[X_{t+1}|X_t]}{\partial\gamma} = aX_{t-1} + b \tag{3.3}$$

$$\frac{\partial E[X_{t+1}|X_t]}{\partial\beta} = c = \gamma(1-e^{-1/\gamma}) \tag{3.4}$$

where $a = \gamma^{-2}e^{-1/\gamma}$ and $b = \beta[1 - \gamma^{-1}e^{-1/\gamma} \ (1+\gamma)]$. Further,

$$\{X_{t+1} - E[X_{t+1}|X_t]\}^2 = \{\rho X_t + \varepsilon_{t+1} - \rho X_t - \beta\gamma(1-e^{-1/\gamma})\}^2$$

$$= \{\varepsilon_{t+1} - E[\varepsilon_{t+1}]\}^2$$

which is independent of $\partial E[X_{t+1}|X_t]/\partial\gamma$ and $\partial E[X_{t+1}|X_t]/\partial\beta$. Then $W = \sigma_\varepsilon^2 V$ and thus $V^{-1}WV^{-1} = \sigma_\varepsilon^2 V^{-1}$. Now from (2.1), (2.2), (3.3), and (3.4),

$$V_{22} = E[c^2] = c^2 \quad ,$$

$$V_{12} = V_{21} = E[acX_{t-1} + bc]$$

$$= ac\beta\gamma + bc \quad ,$$

$$V_{11} = a^2E[X_{t-1}^2] + 2\ ab\ E[X_{t-1}] + b^2$$

$$= a^2\gamma\ (\frac{\lambda\delta}{2} + \beta^2) + 2ab\beta\gamma + b^2$$

since $E[X_{t-1}^2] = \text{Var}\ [X_{t-1}] + (E[X_{t-1}])^2 = \frac{\lambda\gamma}{2}\delta + \lambda^2\mu_y^2\ \gamma = \gamma(\frac{\lambda\delta}{2} + \beta^2)$.

To minimize the nonlinear function (3.2) we can use initial values $\hat{\gamma}^*$ from (3.1) and $\hat{\beta}^* = \hat{\lambda}\hat{\mu}_y^*$ where $\hat{\lambda} = K/T$ as above and $\hat{\mu}_y^*$ is the average of the heighths observed in the time interval containing the start of an episode. Thus $\hat{\mu}_y^*$ will be biased downward but $\hat{\beta}^*$ should suffice as a starting value for β.

To obtain asymptotically correct confidence intervals for γ and β we can evaluate $\sigma_\varepsilon^2\ V^{-1}$ with $\hat{\sigma}_\varepsilon^2$ from (3.1) and $\hat{\lambda}$, $\hat{\mu}_y$, $\hat{\gamma}$, and $\hat{\delta} = \sigma_\varepsilon^2/(\hat{\lambda}\frac{\hat{\gamma}}{2}(1-e^{-2/\hat{\gamma}})$ replacing σ_ε^2, λ, μ_y, γ, and δ.

To obtain confidence intervals for μ_Y we can use the facts that $\mu_y = \beta/\lambda$, that $\hat{\lambda}\xrightarrow{P}\lambda$ and that $\hat{\beta}$ is asymptotically normal. Thus $\hat{\mu}_y$ is asymptotically normal with asymptotic variance $1/\lambda^2$ times the asymptotic variance of $\hat{\beta}$.

We illustrate these ideas in the next section.

4. A WORKED EXAMPLE

In table 1 we give the values of LH in a cow at 10 minute intervals for 24 hours. We note the occurrence of K=8 episodes in the T=144 points with the episodes occurring during the 13th, 42nd, 58th, 69th, 89th, 100th, 115th, and 132 nd time intervals. Thus we estimate λ by $\hat{\lambda} = K/T = 8/144 = .056$ occurrences per 10 minutes or 8 per day and using the Poissoness of K, we get an exact 90% confidence interval for λT as the interval [4.0, 14.5]. The assumption of Poisson occurrences can also be tested by (see Parzen (1962), p. 141) comparing the statistic

$$Z = \frac{\sum_{m=1}^{K} \tau_m - \frac{KT}{2}}{\sqrt{\frac{KT^2}{12}}} = \frac{618 - 576}{117.58} = .36$$

with the critical values of the N(0, 1). Thus the LH data is clearly consistent with the hypothesis of Poisson occurrences.

The initial estimator of γ given by the ordinary autoregressive analysis is $\hat{\gamma}^* = 2.50$ which is consistent with the observation that it takes about 8 or 10 intervals for the episode to decay back to the baseline. The initial estimator $\hat{\mu}_y^* = 20.5$ and thus $\hat{\beta}^* = \hat{\lambda}\hat{\mu}_{\bar{y}}^* = 1.14$. Then using the IMSL Subroutine ZXSSQ to minimize (3.2), we obtain $\hat{\gamma} = 2.50$ and $\hat{\beta} = 1.90$ and thus $\hat{\mu}_y = 33.93$, a considerable increase over $\hat{\mu}_y^*$.

The estimator $\hat{\sigma}_\varepsilon^2$ of $\sigma_\varepsilon^2 = \lambda\delta \frac{\gamma}{2} (1-e^{-2/\gamma})$ obtained from the autoregressive analysis is $\hat{\sigma}_\varepsilon^2 = 29.57$, from which we obtain $\hat{\delta} = \hat{\sigma}_\varepsilon^2/[\hat{\lambda}\hat{\gamma}/2(1-e^{-2/\hat{\gamma}})] = 386.59$. Then substituting $\hat{\sigma}_\varepsilon^2$, $\hat{\delta}$, $\hat{\lambda}$, $\hat{\gamma}$, and $\hat{\beta}$ into σ_ε^2 and V, we have that $\hat{\gamma}$ and $\hat{\beta}$ are approximately normal with means γ and β and variances .00153 and .00123

respectively, from which we have asymptotic 95% confidence intervals (2.42, 2.58) and (1.83,1.97) for γ and β respectively. Finally the asymptotic variance of $\hat{\mu}_y$ is approximately Var $(\hat{\beta})/\hat{\lambda}^2 = .39$ and thus an asymptotic 95% confidence interval for μ_y is (32.67, 35.19).

REFERENCES

Klimko, L. A. and Nelson, P. I. (1978). "On Conditional Least Squares Estimation for Stochastic Processes," Annals of Statistics, 6, 629-642.

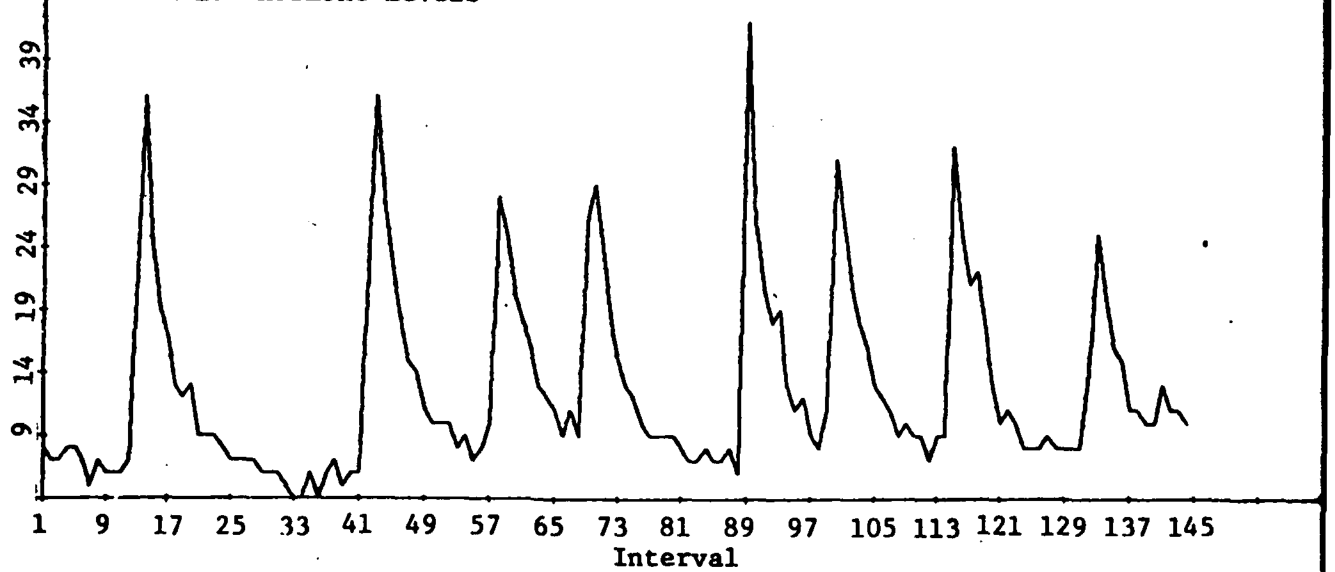
Parzen, E. (1962a). "Spectral Analysis of Asymptotically Stationary Time Series," Bull. Inst. International Statistics, 39, 87-103.

________. (1962b). Stochastic Processes, San Francisco: Holden-Day.

Table 1. LH Levels Every 10 Minutes for 24 Hours

No.	Val.	No.	Val.	No.	Val.	No.	Val.	No.	Val.	No.	Val.
1	8	25	7	49	11	73	15	97	9	121	10
2	7	26	7	50	10	74	13	98	8	122	11
3	7	27	7	51	10	75	12	99	11	123	10
4	8	28	7	52	10	76	10	100	31	124	8
5	8	29	6	53	8	77	9	101	26	125	8
6	7	30	6	54	9	78	9	102	21	126	8
7	5	31	6	55	7	79	9	103	18	127	9
8	7	32	5	56	8	80	9	104	16	128	8
9	6	33	4	57	10	81	8	105	13	129	8
10	6	34	4	58	28	82	7	106	12	130	8
11	6	35	6	59	25	83	7	107	11	131	8
12	7	36	4	60	20	84	8	108	9	132	14
13	22	37	6	61	18	85	7	109	10	133	25
14	36	38	7	62	16	86	7	110	9	134	20
15	24	39	5	63	13	87	8	111	9	135	16
16	19	40	6	64	12	88	6	112	7	136	15
17	17	41	6	65	11	89	42	113	9	137	11
18	13	42	22	66	9	90	26	114	9	138	11
19	12	43	36	67	11	91	21	115	32	139	10
20	13	44	27	68	9	92	18	116	25	140	10
21	9	45	22	69	26	93	19	117	21	141	13
22	9	46	18	70	29	94	13	118	22	142	11
23	9	47	15	71	24	95	11	119	18	143	11
24	8	48	14	72	18	96	12	120	13	144	10

FIGURE 1. Hormone Levels



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